



Munich Personal RePEc Archive

Effects of interactions among social capital, income, and learning from experiences of natural disasters: A case study from Japan

yamamura, eiji
<institution>

13. July 2009

Online at <http://mpa.ub.uni-muenchen.de/16223/>
MPRA Paper No. 16223, posted 14. July 2009 / 11:21

Effects of interactions among social capital, income, and learning from experiences of natural disasters: A case study from Japan

ABSTRACT

This paper explores how and the extent to which social capital has an effect on the damage resulting from natural disasters. It also examines whether the experience of a natural disaster affects individual and collective protection against future disasters. There are three major findings. (1) Social capital reduces the damage caused by natural disasters. (2) The risk of a natural disaster makes people more apt to cooperate and therefore social capital is more effective to prevent disasters. (3) Income is an important factor for reducing damage, but hardly influences it when the scale of a disaster is small.

Keywords: Social Capital, Learning, Natural disaster

JEL classification: H41, P16, Z13

INTRODUCTION

A growing number of empirical works in the social sciences, including economics, have attempted to investigate issues regarding natural disasters (e.g., ALBALA-BERTLAND, 1993; BURTON et al., 1993; GARRET and SOBEL, 2003; TOL and LEEK, 1999)¹. One feature of natural disasters is that they cannot be perfectly forecasted since they are related to various underlying causes. This uncertainty obviously increases the potential economic risks. Hence, SAWADA and SHIMIZUTANI (2007) explored consumption insurance against natural disasters. Such an exogenous shock is likely to have tremendous effect on the degree of investment in physical and human capital, thereby affecting economic growth (SKIDMORE and TOYA, 2002)². Because of these features, humans fail to control for the occurrence of a natural disaster. Recent research, however, provides evidence that the degree of economic development, captured by the quality of institutions, social heterogeneity, social capital, and per capita income, has an important effect on the outcomes of natural disasters, although it cannot prevent them (e.g., ANBARCI et al., 2005; BOLIN 1982; BURTON et al., 1993; ERIKSON 1994; ESCALERAS et al., 2007; FUKUYAMA 2001; GROOTAERT 1998; KAHN, 2005; TOL and LEEK, 1999; TOYA and SKIDMORE, 2007).

¹ As well, a growing number of reports on hurricane Katrina have been published (e.g., CONGLETON, 2006; SHUGART II 2006; SOBEL and LEESON, 2006; EWING et al., 2007; LANDRY, 2007; CHAPPELL, 2007; BOETTKE, 2007; WHITT and WILSON, 2007; ECKEL, 2007).

² The occurrence of natural disaster can be considered as an exogenous shock since it is impossible to predict exactly the date and place of a natural disaster. Nevertheless, the extent of damage from a natural disaster would be a function of physical equipment and the prior attitude of residents towards natural disasters.

Public sector corruption leads contractors to ignore a country's building codes and so buildings often fall short of the appropriate construction standards. This is a reason why public sector corruption is positively associated with earthquake deaths (ESCALERA et al., 2007). Institutional quality seems to be reflected in the degree to which a country is based on democracy. The evidence presented by KAHN (2005) shows that countries with a more democratic political system suffer less deaths from natural disasters. ANBARCI et al. (2005) suggest that, economic inequality hampers the collective action required to save lives when a natural disaster occurs. As a consequence, economic inequality has a detrimental effect on mitigating disaster damage. On the other hand, I focus on the social capital that is defined in this paper as 'a broad term encompassing the norm and networks facilitating collective action for mutual benefit' (WOOLCOOK 1998, p.155). Hence, social capital is likely to promote people to participate in civic life and so take collective action, resulting in economic benefit³. Social capital is found to be more easily formed in a society where economic and ethnic heterogeneity is smaller (ALESINA and LA FERRARA, 2000; COSTA and KAHN, 2003; VIGDOR, 2004, YAMAMURA, 2008b)⁴. As a result, social capital is expected to mitigate the damage caused by disasters via the enhancement of collective action. Little attention has, however, been given to the role of social capital on the alleviation of damage from a natural disaster.

³ A number of reports have attempted to investigate social capital in the modern society (e.g., KNACK and KEEFER, 1997; PUTNAM, 2000; O'BRIEN et al., 2005; WESTERN et al., 2005; BERGGREN and JORDAHL, 2006; MILES and TULLY, 2007; BIRCH and WHITTAM, 2008).

⁴ Generalized trust profoundly associated with social capital also depends on the features of the social structure (LEIGH, 2006a; 2006b; BJÓRNSKOV, 2006).

Prior to natural disasters, people with a great amount of relevant information are less likely to suffer serious damage than those with less knowledge⁵. Reports (JOVANOVIĆ, 1982; JOVANOVIĆ and NYARKO, 1996; LUCAS, 1993) note that learning from past experience possibly enhances the accumulation of human capital, leading to economic growth. The argument of JOVANOVIĆ (1982) that a corporate entity knowing the optimal cost structure based upon a Bayesian learning process is similar in that an economic entity can more efficiently allocate resources through its experience. Such a learning mechanism is also considered to be applicable to the way natural disasters are dealt with⁶. That is to say, people who have experienced natural disasters can obtain correct information about protecting against such events or getting out of them (ANBARCI et al., 2005; ESCALERAS et al, 2007)⁷.

Experience of disasters appears to be helpful for mitigating disaster damage, not only at individual and government levels, but also at the community level. People seem to learn from their experiences of disasters and obtained relevant information about how a community member can take collective action to protect against them, and how the degree to which cooperative behavior benefits an individual by reducing

⁵ DYNES pointed out “the reason people do not make an effort is because they are unaware of the threat or because they lack good information (knowledge) about the risks. This, increasing awareness and information will result in appropriate mitigative behavior” (DYNES 2002, p.38).

⁶ This paper mainly restricts its attention to the prior attitude towards disaster; that is, preparation for a natural disaster. However, it is also important to investigate how a community recovers from disaster (BOLIN and STANFORD 1998, KANIASTY and NORRIS 1995).

⁷ It should be noted that there is a possibility that experience of natural disasters has a detrimental effect on resilience since those who have successfully weathered an event do not feel that they need to evacuate when faced with another such one.

damage. Therefore, prior information about protection against disasters is considered to have an important effect on the efficacy of social capital to reduce disaster damage. Nevertheless, studies dealing with the determinants of damage arising from natural disasters do not pay much attention to how social capital is associated with the collective learning effect. The purpose of this paper is to examine the extent to which social capital and the experience of natural disasters reduce damage. As well, it examines whether experience leads social capital to be more effective in mitigating damage. Furthermore, although Japan is a developed country, Japan society remains relatively homogeneous and social capital deeply accumulated; therefore, people are more inclined to take collective action (YAMAMURA, 2008b). Such a feature of Japan allows me to test how and the extent to which social capital is effective in a developed country.

The organization of this paper is as follows: Section 2 briefly surveys relationships between social capital and natural disasters, and advances a testable hypothesis. Section 3 presents a simple econometric framework. Section 4 discusses the results of the estimations. The final section offers concluding observations.

SOCIAL CAPITAL AND NATURAL DISASTERS

Occurrences of natural disasters are unequally distributed around the world. As they are over concentrated in some areas, the importance of disaster measures differs among countries. According to the CABINET OFFICE, GOVERNMENT OF JAPAN (2007), 21 % of earthquakes of magnitude 6 and over occurred in Japan, although Japan

landmass is only 0.25% of World's⁸. This implies that, compared with other countries, Japan should frequently suffer earthquake related natural disasters and therefore economic loss resulting from these should be recognizable. Therefore, protection against such damage is considered a central issue of economic policy. Compared to countries bordered by other ones, Japan's island condition is a natural limiting factor on the inflow of foreigners and influences from other cultures⁹. Therefore Japanese society continues to be relatively homogeneous. The more homogeneous a society is, the easier it is for collective action to take place and the more profoundly people trust each other (ALESINA and LA FERRARA, 2000; 2002). Ethnic and economic fragmentation are reported to have detrimental effects on damage arising from natural disasters, leading to increases in fatalities (ANBARCI et al., 2003; KAHN, 2005). If this is the case, it is cogent to examine how Japan, characterized by a homogeneous society and frequent earthquakes, copes with natural disasters (HORWICH, 2000; SAWADA and

⁸ Japan incurred 13 % of the total amount of damage resulting from natural disasters worldwide during the past 30 years (CABINET OFFICE, GOVERNMENT OF JAPAN, 2007).

⁹ YAMAMURA (2008b) indicated that the Hirfindahl-type index used of the ethnic fragmentation of Japan is 0.02. As suggested in ALESINA et al. (2003), the value of Japan is smaller not only than that of the USA (0.49) but also the UK (0.12) characterized by the same island geography as Japan. A historical feature of Japan that illustrates an important difference from the UK should be considered to explain how the homogeneous Japanese character was formed. It is widely understood that the rulers of Japan during the Tokugawa period between 1639 and 1859 adopted a closed door policy (SUGIYAMA, 1987). The policy of seclusion was initiated as a response to the perceived threat posed by Christian converts in Japan. Such a policy aided by Japan's island geography is thought to have formed the fundamental homogeneous feature of Japanese society, which has persisted even after Japan opened up to world trade and to international exchanges.

SHIMIZUTANI, 2007)¹⁰. That is to say, under conditions where the population is racially homogenous, this research allows me to investigate how and the extent to which differences of age and the structure of wealth have effects on the outcomes of natural disasters. Information about how people and government become better at coping with disasters, an ability that is obtained through experience, is considered to play a critical role in mitigating the damage arising from a disaster (ANBARCI et.al., 2005; ESCALERAS et al., 2007). An example is the Kobe, Japan, earthquake “The earthquake struck a community, almost no member of which expected it. It has been almost a millennium since an event of comparative magnitude had occurred in the Kansai (Kobe-Osaka-Kyoto). Even business and agencies that had previously drawn up emergency plans were caught by surprise and were unable to implement them” (HORWICH, 2000. p.529). Under such conditions, local government agencies were unprepared and so failed to coordinate the inflow of goods and services from outside the stricken area (HORWICH, 2000)¹¹. This was in part because of the lack of experience of a natural disaster in Kobe¹².

Delays in the initial response by the local government system were singled out for criticism in the aftermath of the Kobe Earthquake. On the other hand, much attention

¹⁰ In Japan, social capital enhances learning from others such as from the diffusion of home computers (YAMAMURA, 2008a), makes a contribution to collective action such as responses to the Census (YAMAMURA, 2008b), and acts as informal deterrents against dangerously driving (YAMAMURA, 2008c).

¹¹ Although governments and many businesses have been ill-prepared for the disasters befalling them, it seems that there is a limit to how prepared they can be in the face of an immense disaster, such as the Kobe earthquake.

¹² During the period of recovery from the Kobe earthquake, the city’s fire department built a new observation and control center and its emergency management process has been reorganized and enlarged (HORWICH, 2000).

was given to role of the informal cooperative activity such as voluntary disaster control organizations in reducing the damage arising from that natural disaster (TIERNERY and GOLTZ 1997). This is probably because voluntary organizations are thought to play important roles in coordinating collective action to reduce damage¹³. An area where people are more inclined to participate in voluntary activity is hence considered to have deeply accumulated social capital (PUTNAM, 2000)¹⁴. There appear to be channels through which experiencing disasters affects social capital and thereby influences victims of disasters. An area that tends to regularly suffer from natural disasters has more inclination to diffuse information concerning preventive measures among its communities; therefore, it reinforces the functions of social capital to cope with risk through collective learning. As a consequence, social capital plays a greater role in mitigating damage from disasters if community members frequently experience such disasters¹⁵. From the discussion as above, two hypotheses can be derived:

¹³ After the Kobe earthquake, the creation of informal support systems against disasters was considered important (SHAW and GODA 2004). Recently, a social network service (SNS) has been tested by the Japanese government with the aim of improving community building and disaster management (SCHELLONG 2007).

¹⁴ PUTNAM (2000) points out that social capital has a positive effect but also has a detrimental one upon human behavior. DURLAUF (1999) asserts that social capital facilitates intragroup coordination by enhancing group identity, which, in turn, may promote intergroup hostility. PELLING (1998) found in a case study of Guyana that marginalized groups continued to be excluded from local participatory decision making in environmental management.

¹⁵ It is also likely that social capital will make a community more resilient; that is, the community is more likely to recover quickly from a disaster. When hurricane Katrina occurred, the Catholic Church in New Orleans helped organize crews of returning residents to assist one another repairing homes (BOETTKE et al., 2007).

Hypothesis 1: An area with highly accumulated social capital has a tendency to have less victims of natural disasters.

Hypothesis 2: Prior experience of disaster reinforces the function of social capital through a learning process, resulting in a reduction of victim numbers¹⁶.

DATA AND METHOD

Data and model

The data set used in this study is a survey panel of 47 prefectures covering 14 years from 1988 to 2001. Table 1 includes variable definitions, means, standard deviations, coefficients of variation, and maximums and minimums of analyzed data. The variables are discussed later. Number of victims, numbers of natural disasters, per capita income, number of fire fighting teams, and the number of immigrants are derived from INDEX PUBLISHING (2006)¹⁷. Data about the numbers of natural disasters used in this research comprise the numbers of roads, bridges, banks that suffered from disasters and the numbers of landslides; all of which can be viewed as outcomes of earthquakes and hurricanes. In this research, under constraints of data limitations, a natural disaster is empirically defined as above¹⁸. Therefore, the

¹⁶ It should be noted that, besides the effects of social capital, the experience of a disaster would have effects on the damage from another natural disaster through various channels. For instance, the disaster experience might lead to better infrastructure and better state policies, both of which are related to learning, but not necessary to social capital.

¹⁷ Victims are defined here as injured persons who need medical care.

¹⁸ It should be noted that whether an earthquake is a disaster or not generally depends

magnitude of an earthquake and the intensity of a hurricane are considered to be reflected in the “number of victims”. There is wide range of intensities of natural disasters such as earthquakes and hurricanes. For instance, earthquakes occur every day but most are too weak to be perceived and therefore have no impact on people. Accordingly, I confront a difficulty in accurately counting natural disasters. The method of counting seems to affect the results and so cause an estimation bias. This is the reason why I considered observable outcomes of a “natural disaster” as disasters¹⁹. The total population number and the population subgroup over 70 years old, the number of those receiving public assistance, the number of policemen, the numbers of houses, public baths, and community centers, are from the ASAHI NEWSPAPER (2004). Some variables, including the numbers of public baths, community centers and fire fighting teams are divided by the population to obtain per capita values. The proportions of elderly and those receiving public assistance are calculated from the number over 70 years old, and the number receiving public assistance divided by the total population number, respectively.

There are several reports that have investigated fatalities in natural disasters (ANBARCI et al. 2005; ESCALERAS et al., 2007; KAHN 2005); however, these cover only a portion of the victims of disasters and so do not accurately reflect the full damage caused²⁰. Thus this paper considers all victims as observed at the moment of an event.

on the extent to which daily life was disrupted and the damage. The “empirical” definition in this paper is different.

¹⁹ The number of intense hurricanes and earthquakes can be obtained from NATIONAL ASTRONOMICAL OBSERVATORY JAPAN (2006). The similar results were provided when these data are used.

²⁰ TOYA and SKIDMORE (2007) explored not only fatalities but also the index of economic damage measured by the estimated damage in real US \$ when disasters

VICTIM, for which this paper attempts to examine determinants, is a non-negative count of victims of natural disasters. As such, a basic, and appropriate, estimation method is the poisson model. However, a shortcoming of the poisson model for this analysis is its assumption of an equal conditional mean and variance for the dependent variable. That is, to be appropriate in our case, the poisson model requires the conditional mean of *VICTIM* to be equal to its variance. As such, the poisson model is best applied in conditions where there is limited variation in the dependent variable. However, from Table 1 it can be seen that maximum and minimum values are 62,085 and 0 respectively, and the standard deviation is 4,314, indicating the variation of the dependent variable is clearly a large one. As well, an over-dispersion of the number of victims is manifest in Table 2, showing the percentile rank. Numbers of victims in the lowest percentile, the 10th percentile, is 1 whereas that of the highest is 1645. Taking table 1 into account, the mean value, 914, is above the 80th percentile. Hence, careful attention must be paid to the over-dispersion of dependent variables when estimations are conducted. In such a situation, the use of a poisson process to estimate typically causes a downward bias in the model's standard errors. In line with reports concerning fatalities arising from natural disasters (ESCALERAS et al, 2007), a negative binominal model should be employed since this model generalizes the poisson process by expressly relaxing the assumption of an equal conditional mean and variance through the introduction of a parameter accounting for any unobserved heterogeneity between observations. What is more, using the zero-inflated negative binominal model introduces a splitting process, thus considering a zero victims account (KAHN, 2005). Estimation by the zero-inflated negative binominal model uses a logit where the

occurred.

dependent variable equals 1 if there is no victim arising from a disaster. The logit model includes the number of natural disasters in year t and the interaction of its account with income.

Function form

Following the discussion above, the estimated function of the number of victims then takes the following form²¹:

$$\begin{aligned} VICTIM_{it} = & \alpha_0 + \alpha_1 NDIS_{it} + \alpha_2 AVDIS_{it} + \alpha_3 PBATH_{it} + \alpha_4 PBATH_{it} * AVDIS_{it} + \\ & \alpha_5 CENTE_{it} + \alpha_6 CENTE_{it} * AVDIS_{it} + \alpha_7 FFIGHT_{it} + \alpha_8 FFIGHT_{it} * \\ & AVDIS_{it} + \alpha_9 POLIC_{it} + \alpha_{10} IMIG_{it} + \alpha_{11} POP_{it} + \alpha_{12} PORAT_{it} + \\ & \alpha_{13} OLDRAT_{it} + \alpha_{14} INCOM_{it} + \nu_t + \omega_{it}, \end{aligned}$$

where $VICTIM$ represents the number of victims in prefecture i in year t , and α 's represents the regression parameters. ν_t represent the unobservable specific effects of year t (a fixed effect time vector) respectively; ω_{it} represents the error term.

As mentioned, the structure of the data set used in this study is a survey panel of 47 prefectures covering the 14 years from 1988 to 2001. Macroeconomic conditions will be captured in ν_t , and I incorporate each year's dummy variables to restrain the time specific effects.

Though it seems obvious, it needs noting that an area can only contain victims of natural disasters if a natural disaster actually takes place there. Following Kahn(2005), in the logit model of the splitting stage where the number of disasters that a prefecture i experiences in year t and its interaction term of the log form of per capita

²¹ Values of coefficients can be interpreted as the elasticity of the number of victims with respect to the corresponding independent variables, which are evaluated at the sample mean values of the variables.

income and population size, which are represented as $NDIS$, $NDIS*Ln(INCOME)$ and $NDIS*Ln(POP)$ respectively, are incorporated as independent variables. The interaction term of a disaster's count with income level and population would account for the possibility that prefectures with higher incomes and smaller populations are less inclined to suffer victims from disasters that occur. $NDIS*INCOME$ and $NDIS*POP$ are thus expected to take positive and negative signs since the logit model estimates the probability that nobody in a given prefecture in a given year becomes a victim of a natural disaster.

I now proceed to discuss determinants of the number of victims. The number of disasters, represented as $NDIS$, in year t and in prefecture i convincingly increases the number of victims and therefore takes a negative coefficient sign. As earlier discussed, people who experience disasters are better able to acquire information useful for preventing the effects of natural disasters, and so to reduce damage through learning processes. To test this hypothesis, $AVDIS$, the average number of disasters occurring in past years is included as an explanatory variable to capture disaster experience²². The choice of the past years seems to have an effect upon the outcomes of estimation. If the prediction is supported, the sign of $AVDIS$ becomes negative. To check the robustness of the results, I use three alternative variables (1) number of disaster occurring in the past year, namely, years $t-1$ in prefecture i , (2) the average number of disasters occurring from years $t-1$ to $t-3$ in prefecture i , (3) the average number of disasters occurring from years $t-1$ to $t-5$ in prefecture i . Furthermore, the importance

²² CABITNET OFFICE, GOVERNMENT OF JAPAN (2007) reports that the past experience of disasters encourage people to take precautions against future disasters, whereas the effect of experience on cautious behavior diminishes as time passes. Therefore, this paper restricts past experiences to those within three years.

of the experience of a natural disaster seems to change as time passes. These alternative variables also allow me to examine how and the extent to which passing time affects residents' behavior against a natural disaster.

There appear to be various ways of measuring the degree of social capital the relevance of proxies for social capital will need to be checked (CALLOIS and AUBERT 2007; WESTERN et al., 2005). As mentioned in the introduction, social capital is a concept covering norms and social networks. According to HAYAMI (2001), norms and social capital are formed through long-term and intensive interpersonal interactions. The intensity of inter-personal interactions should thus be captured when social capital is measured, especially in the Asian (Japanese) context. Therefore, the influence of social capital can be considered to be limited within a local community. Considering this point, the following independent variables are used as proxies of social capital²³.

In traditional Japanese daily life, public baths were used by community members who, apart from the wealthy, ordinarily lived in houses without a private bath. Through the use of such baths people could get acquainted with neighbors and generate a social network. In modern Japan, most residences have their own baths, and people are therefore more likely to take a bath at home. However, a new type of public bath featuring more deluxe baths and saunas has recently developed, and these are used by all sectors of society, thus providing a place to meet neighbors and form social capital

²³ Existing literature mainly concerns western countries, variables such as newspaper reading, volunteer activity, and voter turnout are considered to capture social capital. They also seem appropriate as surrogate social capital in Japan (YAMAMURA 2009); however, these variables are not available every year. Therefore they cannot be incorporated in this paper since the data set of this paper is a panel structure that requires annual data.

(YAMAMURA, 2008a). The number of public baths, represented as *PBATH*, can thus serve as a proxy for social capital. Therefore, the signs of *PBATH* are predicted to be negative. People are more likely to trust each other and then take collective action if there is a place where they can communicate with each other and if the community is well organized (PUTNAM, 2000). *CNETE*, which is the number of community centers, is a proxy for social capital. Hence, the signs of *CENTE* are expected to be negative.

Earthquakes, as one of their results, are likely to entail fires as secondary events. Modern Japanese society is rooted in a system of group responsibility within a community. For instance, the community fire-fighting team, represented as *FFIGHT* originated in the Edo period and continues today (GOTO, 2001). Community fire-fighting teams, informal institutions, are still called for today because of the scarcity of public firehouses, which are regarded as formal institutions, and hence act as substitutes for public firehouses. What is more, these teams play an important role, not only in deterring fire but also in generating social capital through interpersonal communication in a cooperative protective activity against disaster (GOTO, 2001). Hence, fire-fighting teams are thought to have an important disaster prevention role. Members belonging to such teams also regularly patrol within their community to ensure that precautions are taken against fire; thereby keeping an eye on the streets, buildings and houses within their community. As a result of such activity, communal fire-fighting teams also function as a vigilant corps so that criminal behavior such as robbery, which is likely to occur after a disaster, is prevented²⁴. As a consequence, the signs of *FFIGHT* are expected to be negative.

²⁴ LEDERMAN et al (2002) uses international data to examine the social capital effect upon crime and suggests that countries with larger social capital are more apt to have reduced crime rates.

As noted before, experience of a natural disaster provides useful information concerning protection against future natural disasters, and then reinforces the function of social capital to take collective action to mitigate damage from a disaster. To test this hypothesis, which is the primary focus of this paper, cross terms between proxies of social capital and experience of disasters need to be checked. That is to say, the signs of $PBATH*AVDIS$, $CENTE*AVDIS$ and $FFIGHT*AVDIS$ are given careful attention and are predicted to become negative.

Police are considered to be the emergency first responder to a natural disaster and therefore $POLIC$ is expected to take negative sign. Frequent movers weaken community ties; therefore, communities with higher rates of residential turnover are less well integrated. This is why residential mobility tends to undermine community-based social capital (PUTNAM, 2000); thereby hampering the collective action required to alleviate damage from a disaster. Hence, it is possible that the coefficients of $IMIG$, which is the number of immigrants from other prefectures arriving during the last year, take a positive sign.

The number of victims is expected to become larger in areas where a larger number of residents live if the scale of the natural disasters is of the same magnitude. Accordingly, the sign of POP representing total population is predicted to become positive. Lower income people are more likely to suffer from a natural disaster since they appear to live in more humble residences. The proportion of poor people thus increases the number of victims of disasters. In Japan, individuals living below a poverty threshold can be in receipt of public assistance so that the proportion of those who are in receipt of public assistance, which is denoted as $PORAT$, is regarded to proxy for the poor people rate. In addition, it seems reasonable that elderly people cannot

make a quick response in an emergency, leading them to become victims. *OLDRAT*, which stands for the proportion of those over 70 years old, is incorporate to capture such an effect. Accordingly, *PORAT* and *OLDRAT* will also take a positive sign.

INCOM, representing per capita income is used to capture economic conditions. The number of victims is expected to become larger in areas where a larger number of residents live if the scale of the natural disasters is of the same magnitude. Areas with higher income are convincingly more able to build earthquake resistant buildings and provide anti-earth quake equipment. Accordingly, the signs of *INCOM* are predicted to become negative.

RESULTS

Tables 3 and 4 present the results of the zero inflated negative binominal estimations. In both tables, columns (1), (4), (7), and (10) show the results when the number of disasters occurring in the past year is used as *AVDIS*. Columns (2), (5), (8) and (11) show the results when the average number of disasters occurring in the past three years is used as *AVDIS*. Columns (3), (6), (9) and (12) show the results when the average number of disasters occurring in the past five years is used as *AVDIS*. To properly compare the results, values presented in the upper panel are the elasticity, which is evaluated at the sample mean values of the dependent and each independent variable. The results of Table 3 were estimated using all samples, 658 observations. As explained before, the zero inflated negative binominal model is employed to take into account the effect of outliers; thus it seems reasonable to ask whether the outcomes of estimations are at least somewhat influenced by outliers. As discussed for Tables 1 and 2 in the previous section, the sample is indeed skewed. To take this into account

and to check the robustness of the outcome presented in Table 4, re-estimations are conducted when samples are restricted to those under 100 victims and therefore the observations become 356.

Logit estimation

In the bottom part of both tables, the results of the logit model of the splitting stage are reported. The cross term of *NDIS* and *POP* shows a negative sign for the coefficient in all estimations. Furthermore, the results of Tables 3 and 4 indicate statistical significance at the 1 % level in all estimations. Although contrary to the prediction, the signs of the cross terms of *NDIS* and *INCOM* become negative, but are not statistically significant in all estimations. Overall, these results are consistent with the prediction that larger population areas are more likely to have victims when a disaster occurs.

Estimation results using all samples

I now discuss the results of the negative binominal model after the splitting stage in Table 3. The significant positive signs of *NDIS* in all estimations of Table 3 are compatible with the prediction. With respect to *AVDIS*, all results show negative signs. As shown in the second row of columns (1) and (2), the fact that *AVDIS* is statistically significant, reveals that the learning effect makes a contribution to decreasing the number of victims. Nevertheless, column (3) is insignificant statistically, and its absolute value of 0.02 is remarkably smaller than those of (1) and (2). It follows from this that past experience reduces victim numbers but its effect diminishes as time passes.

With respect to the proxies for social capital, in columns (1), (2) and (3), *CENTE*, *PBATH* and *FFIGHT* take the anticipated negative sign of *CENTE*. In particular, *CENTE* is significant at the 1 % level. This indicates that social capital alleviates damage from disasters. Any insignificance of *PBATH* and *FFIGHT* are likely to be driven by potential shortcomings such as the skewness of the sample caused by outliers²⁵. To investigate the learning effect through the experience of a disaster on the effectiveness of social capital, I check the results of the cross term of *AVNDIS* with proxies of social capital such as *PBATH*AVNDIS*, *CENTE*AVNDIS* and *FFIGHT*AVNDIS*. As predicted previously, in all the of the interaction terms, their signs become negative. They become statistically significant when past experience is measured by the number of disaster occurring in the past year and in the past three years, but they become insignificant in the case using the number in the past five years. Furthermore, as shown in column (6), the absolute value of *PBATH * AVDIS*, which is 0.01 for both, is distinctly smaller than in columns (4) and (5), which are 0.06 and 0.04, respectively. The same tendency is observed concerning *CENTE * AVDIS* in columns (7)-(9) and *FFIGHT * AVDIS* in columns (10)-(12), indicating that the absolute values when *AVDIS* is calculated by the natural disasters in the past five years are by far smaller than the other values. Restricting attention to the results in the case that *AVNDIS* is calculated by data of the past year and the past three years, the absolute values of *AVDIS* and its interaction terms are between 0.04 and 0.08, indicating their elasticity is relatively modest. In line with the prediction, these results imply that the

²⁵ Another possible reason for their unpredicted can be found in the argument of LEDERMAN et al. (2002), that the indicators of social capital they defined reflect both group-specific and society-wide social capital, which are expected to promote and reduce collective action, respectively. Therefore these opposite effects neutralize each other.

experience of a disaster accumulates the human capital necessary to protect against a future one; this then reinforces the function of social capital to coordinate collective action when a disaster occurs. Nevertheless, such an interaction effect has a tendency to disappear as time passes.

Contrary to the prediction, the signs of *POLIC* become positive, though insignificant, meaning that the police did not make a contribution to a reduction of victims. In all estimations, the significant negative signs of *IMIG* suggested that a decay of social capital causes impediments to the success of collective action, thereby increasing the number of victims.

Consistent with the prediction, in all estimations, *POP* take significant predicted signs and their values are larger than 4. As well, *PORAT* and *OLDRAT* take their anticipated signs although *PORAT* are not significant; indicating that poor and old individuals are more inclined to suffer from disasters. *INCOM* take their significant predicted signs and their values are larger than 3. From this can be derived the fact that the economic condition tremendously affects on the number of victims. Especially, the fact that if income rises 1 %, the number of victims decreases by about 4 %; reflecting that areas with higher incomes can to a large extent afford to protect against disasters.

Estimation results with the victims restriction

The determinants of the number of victims appear to depend on the magnitude of the disaster, while the skewness of the sample seems to influence the results, as argued by ESCALERAS et al. (2007). For a closer examination to take into these issues into account, I re-estimated using the same model but in which samples were

restricted to a number of victims smaller than 100²⁶. These results are shown in Table 4. Looking at columns (1) and (2) reveals in regard to *AVNDIS*, as reported in the second row, significant negative signs and the value of the coefficient. Column (3) suggests insignificance and a smaller value. Turning to the effects of social capital as captured by *PBATH*, *CENTE*, and *FFIGHT*, with the exception of *PBATH*, the coefficient signs become negative. These results are almost the same when all samples are used, as discussed before. It follows from the results discussed so far that not only a learning effect but also social capital are negatively associated with the number of victims resulting from natural disasters.

Switching attention to columns (4)-(12), where the cross terms of disaster experience and social capital are reported, I next examine how the learning effect reinforces social capital. Consistent with the prediction, all signs of *PBATH*AVNDIS*, *CNETE*AVNDIS* and *FFIGHT*AVNDS* are negative, and are equivalent to those presented in Table 3. In terms of the absolute values of the coefficients shown in columns (4),(5), (7),(8),(10), and (11), *AVDIS* and its interaction terms are between 0.02 and 0.06, suggesting they are almost at the same level as in Table 3. On the other hand, when I used *AVNDIS* calculated using data from the past five years, they are not statistically significant and the absolute values become pronouncedly smaller. Taken together, the impacts on disaster damage of learning, social capital and their interaction do not disappear even when the scale of natural disasters is small, so long as the focus is on disaster experiences limited to those within a few years. Put another way, these

²⁶ While the estimation results shown in table 3 are based on the zero-inflated negative binominal model designed to take into account the effect of outliers, it seems reasonable to question whether the outliers matter since the sample is skewed as mentioned previously.

effects are stable regardless of which samples are used and so are not affected by the scale of a disaster. Hence, the estimation results concerning *Hypotheses 1* and *2* are robust under the different samples, indicating that *Hypotheses 1* and *2* are strongly supported. Nevertheless, it is very interesting to observe that these effects diminish strikingly when I take more distant past events into account. According to the CABINET OFFICE, GOVERNMENT OF JAPAN (2007), people in Japan are likely to take measures to cope with a natural disaster immediately after they experience a disaster but cease from doing so as time passes. From this I derive the argument that the precautions against the risk of a disaster surge as an outcome of a disaster experience but then gradually decrease over time. The findings I have presented thus far are considered to reflect the feature of human behavior pointed out by the CABINET OFFICE, GOVERNMENT OF JAPAN (2007).

I found it interesting that the coefficients of *INCOM* in Table 4, contrary to expectations, take positive signs in all columns. Accordingly, in respect to the per capita income, there is remarkable difference from those reported in Table 3 showing negative significant signs. What is more, the coefficient values *INCOM* are smaller than 1.00; far smaller than those shown in Table 3. I derived from this that economic conditions are not associated with disaster damage when disasters are small in scale. Combining the estimation results in Tables 3 and 4 indicates that the effects of economic conditions on disaster damage are affected by the restriction of samples. The fact that higher incomes are more likely to reduce the number of victims does not persist when samples are restricted to a small number of victims. I interpret these results as follows. According to the theoretical model developed by ANBARCI et al. (2005), the per capita level of income increases the provability of collective action in the

form of the creation and enforcement of building codes, appropriate professional licensing, and earthquake-sensitive zoning²⁷. That is, areas where income is at a high level have more ability to cope with natural disasters, mainly through the intensification of physical structures such as the provision of earthquake-resistant buildings, fire proof-buildings, and/or fire-prevention equipment. Such measures seem to be effective in alleviating the damage when inordinate scale disasters strike buildings. In the case where the magnitude of a disaster is, however, too modest to damage the physical structure, economic conditions such as per capita income do not affect outcomes.

To sum the evidence presented so far; factors concerning disaster experience and social capital for reducing disaster damage persist even with the different samples²⁸. However, per capita income has tremendous effects on any resulting damage, though this relationship disappears because of the restriction of our samples. The evidence above seems to indicate that informal cooperative activity promoted through accumulation of social capital plays an important role in alleviating disaster damage, especially in cases where the disaster is not of a large scale, being one in which economic factors can make no contribution to the reduction of damage.

²⁷ The collective action required here is different from that required for informal voluntary activity promoted by social capital.

²⁸ Various factors, such as policy making and investment for physical equipment, which are not considered in this research, are however thought to have made a contribution to the results. Thus, care is needed in interpreting these results and the findings observed in this study will require future scrutiny.

CONCLUSION

It is impossible to control the occurrences of natural disasters, but it is possible to alleviate damage to some extent. An example is taking protection action against a future natural disaster; indeed, this is an area where local government is expected to assume an important role in coping with disasters. Nevertheless, the Kobe earthquake case in Japan shows what can go wrong; in that event, the initial response system of the local government organs was delayed and indeed malfunctioned, whereas informal cooperative activity such as voluntary disaster control organizations responded promptly, resulting in a reduction of the damage arising from this natural disaster. To reduce damage, collective action is called for and voluntary organizations are important. Therefore, informal organizations are likely to decrease damage through their collective action in areas where there is high social cohesion and therefore people are more inclined to participate in voluntary activities.

Through experiencing a natural disaster, individuals may learn the how to deal with a future natural disaster. As well, this experience is apt to change the attitude of individuals regarding disasters. As larger amounts of information concerning natural disasters are obtained, individuals are more likely to perceive latent damage resulting from a lack of appropriate measures, and therefore take steps to cope.

The main aim of this paper has been to examine how and the extent to which the experience of a natural disaster, social capital, and their interaction are related with damage resulting from natural disasters measured by the number of victims. To this end, using prefecture level data of Japan for the years between 1988 and 2001, this

paper ascertained the determinants of the number of victims of natural disasters. The major findings from this study were: (1) Social capital reduces damage resulting from natural disasters. (2) Abundant information concerning natural disasters obtained through past experiences makes people more apt to cooperate and therefore social capital becomes more effective to prevent disasters. Nevertheless, it becomes less effective as time passes after the experience of a disaster. (3) A high level of income makes much more contribution than social capital to a reduction in the number of victims; nevertheless, the level of income hardly affects the number of victims in small scale disasters, hence social capital makes a greater contribution in this situation.

From the estimations here, I derived an argument that, in general, physical equipment and infrastructure against disasters are more effective than cooperative behavior, namely collective action, among people. By contrast, cooperative behavior becomes relatively more effective in small scale disasters. What is more, thanks to a spillover of information about natural disasters, cooperative behavior is thought to be more easily organized, thereby reducing the damage resulting from such a disaster. The positive effect of the disaster experience on cooperative behavior deteriorates as time passes after people experience a disaster, because people decrease their precautions against a future disaster. It follows from this that a government should not only provide physical equipment, but should also make efforts to transmit more information about natural disasters to stimulate and promote collective action by its citizens against disaster.

This study uses aggregated-level data at a prefecture level and so individual responses to natural disasters cannot be considered. Further, I consider the experience of suffering disasters to be a proxy for the quantity of information about disasters

obtained by people. This assumption, however, may not be sufficiently convincing. Accordingly, a more appropriate measure for the information acquired by people prior to disaster is called for. As well, this paper did not capture the influence of the experience of disaster on improvements of infrastructure and policy. For a better understanding of the findings in this paper, more purposefully constructed individual-level data needs to be obtained and the various latent effects of the disaster experience should be controlled for. These are issues remaining to be addressed in future study.

REFERENCES

- ALBALA-BERTRAND J. (1993) *Political Economy of Large Natural Disasters*. Oxford University Press, New York.
- ALESINA A. and LA FERRARA E. (2000) Participation in heterogeneous communities, *Quarterly Journal of Economics* **115**, 847-904.
- ALESINA A. and LA FERRARA E. (2002). Who trust others? *Journal of Public Economics* **85**, 207-234.
- ALESINA A., DEVLEESCHAUWER A. KURLAT S. and WACZIAG R. (2003) Fractionalization, *Journal of Economic Growth* **8**, 155-194.
- ANBARCI N., ESCALERAS M. and REGISTER C. (2005) Earthquake fatalities: the interaction of nature and political economy, *Journal of Public Economics* **89**, 1907-1933.
- ASAHI NEWSPAPER. (2004) *Minryoku: Todofuken-betsu Minryoku Sokutei Shiryoshu* (CD-ROM edition), Asahi-Newspaper, Tokyo..
- NATIONAL ASTRONOMICAL OBSERVATORY JAPAN. (2006). *Rika Nenakan. (Chronological Scientific Tables)*, National Astronomical Observatory, Tokyo.
- BERGGREN N. and JORDAHL H. (2006) Free to trust: Economic freedom and social capital, *Kyklos* **59**, 141-169.
- BIRCH K. and WHITTAM G.(2008) The third sector and the regional development of social capital, *Regional Studies* **42(3)**, 437-450.
- BJØRNSKOV C. (2006) Determinants of generalized trust: A cross-country comparison, *Public Choice* **130**, 1-21.
- BOETTKE P., CHAMLEE-WRIGHT E., GORDON P., IKEDA S., LEESON P T., and

- SOBEL R. (2007) The political, economic, and social aspect of Katrina, *Southern Economic Journal* **74**, 363-376.
- BOLIN R. (1982) *Long-Term Family Recovery from Disaster*, University of Colorado, Boulder.
- BOLIN R., STANFORD L. (1998) The Northridge earthquake: community-based approaches to unmet recovery needs, *Disasters* **22**, 21-38.
- BURTON K., KATES R. and WHITE G. (1993) *The Environment as Hazard*, 2nd edition, Guilford Press, New York.
- CABINET OFFICE, GOVERNMENT OF JAPAN. (2007) *A Disaster Prevention White Paper*. (In Japanese) Cabinet Office, Government of Japan.
<http://www.bousai.go.jp/hakusho/h19/index.htm>
- CALLOIS, J M. and AUBERT F. (2007). Towards indicators of social capital for regional development issues: The case of French rural areas, *Regional Studies* **41**, 809-921.
- CHAPPELL W F., FORGETTE R G., SWANSON D A. and VAN BOENING M V. (2007) Determinants of government aid to Katrina Survivors: evidence from survey data, *Southern Economic Journal* **74**, 344-362.
- CONGLETON R D. (2006) The story of Katrina: New Orleans and the political economy of catastrophe, *Public Choice* **127**, 5-30.
- COSTA D. and KAHN M. (2003) Civic engagement in heterogeneous communities, *Perspectives on Politics* **1**, 103-112.
- DYNES R. (2002). The importance of social capital in disaster responses, University of Delaware, Disaster Research Center, Preliminary Paper #327.
- DURLAUF S. (1999) The case 'against' social capital, *Focus* **20**, 1-5.

- ECKEL C., GROSSMAN P J. and MILANO A. (2007) Is More information always better? An experimental study of charitable giving and hurricane Katrina, *Southern Economic Journal* **74**, 388-411.
- ERIKSON, K. (1994) *A New Species of Trouble: Explorations in Disaster, Trauma, and Community*, W.W. Norton and Company, New York.
- ESCALERAS M., ANBARCI N. and REGISTER C. (2007) Public sector corruption and major earthquakes: A potentially deadly interaction, *Public Choice* **132**, 209-230.
- EWING B T., KRUSSE J B. and SUTTER D. (2007) Hurricanes and economic research: An introduction to the Hurricane Katrina Symposium, *Southern Economic Journal* **74**, 315-325.
- FUKUYAMA, R. (2001) Social Capital, Civic Society and Development, *Third World Quarterly* **22**, 7-20.
- GARRET T. and SOBEL R. (2003) The political economy of FEMA disaster Payments, *Economic Inquiry* **41**, 496-509.
- GOTO I. (2001) *Tracing the Origin of the Communal Fire-fighting team: Communal fire- fighting Teams in the 21st Century (Shobo-dan no Genkryu o Tadoru: 21seki no Shobo-dan no Arikata)*, Kindaishobo-sha, Tokyo.
- GROOTAERT C. (1998) Social capital: the missing link the world bank, social development family, environmentally and socially sustainable development network, Social Capital Initiative, Working Paper 3.
- HAYAMI Y. (2001). *Development Economics: From the Poverty to the Wealth of Nations*. Oxford University Press, New York.
- HORWICH G. (2000) Economic lessons from the Kobe earthquake, *Economic*

Development and Cultural Change **48**, 521-542.

INDEX CORPORATION. (2006) *Chiiki toukei* 2006 (CD-ROM edition), Index corporation, Tokyo.

JAPAN BROADCASTING CORPORATION. (1979, 1996) *Zenkoku Kenmin Ishiki Chosa*, Japan broadcasting corporation, Tokyo.

JOVANOVIC B. (1982). Selection and evolution of industry, *Econometrica* **50**, 649-670.

JOVANOVIC B. and Nyarko Y. (1996) Learning by doing and the choice of technology, *Econometrica* **64**, 1299-1310.

KAHN M. (2005) The death toll from natural disasters: the role of income, geography, and institutions, *Review of Economics and Statistics* **87**, 271-284.

KANIASTY K and NORRIS F H. (1995) In search of altruistic community: patterns of social support mobilization following Hurricane Hugo, *American Journal of Community Psychology* **23**, 447-477.

KNACK S. and KEEFER P. (1997) Does social capital have an economic payoff? *Quarterly Journal of Economics* **112**, 1251-1288.

LANDRY C E., BIN O., HINDSLEY P., WHITEHEAD J C. and WILSON K. (2007) Going home: Evacuation-migration decisions of hurricane Katrina survivors, *Southern Economic Journal* **74**, 326-343.

LEDERMAN D., LOAYZA N. and MENÉNDES M. (2002) Violent crime: Does social capital matter? *Economic Development and Cultural Change* **50**, 509-39.

LEIGH A. (2006a) Does equality lead to fraternity? *Economics letters* **93**, 121-125.

LEIGH A. (2006b) Trust, inequality, and ethnic heterogeneity, *Economic Record* **82**, 268-280.

- LUCAS R.E. (1993). Making a miracle. *Econometrica* **61**, 251-272.
- MILES N. and TULLY J. (2007) Regional Development Agency Policy to Tackle Economic Exclusion? The Role of Social Capital in Distressed Communities, *Regional Studies* **41(6)**, 855-866.
- O'BRIEN., DAVID J., PHILLIPS J.L. and PATSIORKOVSKY V. (2005). Linking indigenous bonding and bridging social capital, *Regional Studies* **39(8)**, 1041-1051.
- PELLING M. (1998) Participation, social capital and vulnerability to urban flooding in Guyana, *Journal of International Development* **10**, 469-486.
- PUTNAM R. (2000) *Bowling Alone: the Collapse and Revival of American Community*, A Touchstone Book, New York.
- SAWADA Y. and SHIMIZUTANI S. (2007) Consumption insurance against natural disasters: Evidence from the Great Hanshin-Awaji (Kobe) earthquake, *Applied Economics Letters* **14**, 303-306.
- SCHELLONG A. (2007). Increasing social capital for disaster response through social networking service (SNS) in Japanese local governments, NCDG Working Paper No. 07-005.
- SHAW R and GODA K. (2004). From disaster to sustainable civic society: the Kobe experience, *Disasters* **28**, 16-40.
- SHUGHART II W.G. (2006) Katrinanomics: The politics and economics of disaster relief, *Public Choice* **127**, 2006, 31-53.
- SKIDMORE M. and TOYA H. (2002) Do natural disasters promote long-run economic growth, *Economic Inquiry* **40**, 664-687.
- SOBEL R.S. and LEESON P.T. (2006) Government's response to hurricane Katrina: A

- public choice analysis, *Public Choice* **127**, 55-73.
- STATISTICS BUREAU OF THE MINISTRY OF INTERNAL AFFAIRS AND COMMUNICATIONS. (various years) *Statistics Bureau of the Ministry of Internal Affairs and Communications. Zenkoku shohi zhittai chosa*, Statistics Bureau of the Ministry of Internal Affairs and Communications, Tokyo.
- SUGIYAMA S. (1987) The impact of the opening of the ports on domestic Japanese industry: The case of silk and cotton. *Economic Studies Quarterly* **38**, 338-353.
- TIERNEY K and GOLTZ J D. (1997). Emergency response: lessons learned from the Kobe earthquake, University of Delaware, Disaster Research Center, Preliminary Paper #260.
- TOL R. and LEEK F. (1999). Economic analysis of natural disasters, In: Downing, T., Olsthoorn, A. and Tol, R. (Eds.), *Climate Change and Risk*, pp.308-327. Routledge, London.
- TOYA H. and SKIDMORE M. (2007) Economic development and the impact of natural disasters, *Economics Letters* **94**, 20-25.
- VIGDOR J.L. (2004) Community composition and collective action: Analyzing initial mail response to the 2000 Census, *Review of Economics and Statistics* **86**, 303-312.
- WESTERN J., STIMSON R., BAUM S. and VAN GELLECUM Y. (2005) Measuring community strength and social capital, *Regional Studies* **39(8)**, 1095-1109.
- WHITT S. and WILSON R.K. (2007) Public goods in the field: Katrina evacuees in Houston, *Southern Economic Journal* **74**, 377-387.

- WOOLCOOK M. (1998) Social capital and economic development: toward a theoretical synthesis and policy framework, *Theory and Society* **27**, 151-208.
- YAMAMURA E.(2008a) Diffusion of home computers and social networks: A study using Japanese panel data. *Applied Economics Letters* **15**, 1231-1235.
- YAMAMURA E.(2008b) The effects of inequality, fragmentation, and social capital on collective action in a homogeneous society: Analyzing responses to the 2005 Japan Census. *Journal of Socio-economics*.**37**, 2054-2058
- YAMAMURA E.(2008c) The impact of formal and informal deterrents on driving behavior. *Journal of Socio-economics* **37**, 2505-2512.
- YAMAMURA E.(2009) Effects of social norms and fractionalization on voting behavior in Japan. Forthcoming in *Applied Economics*.

Table 1 Variable definitions and descriptive statistics

Variable	Definition	Mean	Standard deviation	Coefficient of variation	Max	Min
<i>VICTIM</i>	Number of victims	914	4314	4.71	62,085	0
<i>NDIS</i>	Number of natural disasters	91	262	2.85	4,898	0
<i>AVNDIS (1 year)</i>	Number of disasters during the past year.	102	289	2.83	4,898	0
<i>AVNDIS (3 Years)</i>	Average number of disasters during the past three years.	103	169	1.63	1,708	1
<i>AVNDIS (5 Years)</i>	Average number of disasters during the past five years.	124	270	2.17	3,516	1.6
<i>PBATH</i>	Per capita number of public baths	$0.21 \cdot 10^{-3}$	$0.07 \cdot 10^{-3}$	0.33	$0.49 \cdot 10^{-3}$	$0.09 \cdot 10^{-3}$
<i>CENTE</i>	Per capita number of community centers	$0.22 \cdot 10^{-3}$	$0.17 \cdot 10^{-3}$	0.77	$0.90 \cdot 10^{-3}$	$0.07 \cdot 10^{-3}$
<i>FFIGHT</i>	Per capita number of fire fighting teams	$0.31 \cdot 10^{-3}$	$0.14 \cdot 10^{-3}$	0.45	$0.62 \cdot 10^{-3}$	$0.04 \cdot 10^{-3}$
<i>POLIC</i>	Number of policemen	4,763	6,536	1.37	42,197	1,069
<i>IMIG</i>	Share of immigrants from other prefectures ^{a)}	$21 \cdot 10^{-3}$	$5 \cdot 10^{-3}$	0.26	$42 \cdot 10^{-3}$	$10 \cdot 10^{-3}$
<i>POP</i>	Population numbers ^{a)}	2,648	2,393	0.90	11,900	616
<i>PORAT</i>	The share of those receiving public assistance	$7.45 \cdot 10^{-3}$	$4.52 \cdot 10^{-3}$	0.606	$28.6 \cdot 10^{-3}$	$1.77 \cdot 10^{-3}$
<i>OLDRAT</i>	The share of elderly over 70 years old.	0.11	0.02	0.24	0.19	0.05
<i>INCOM</i>	Per capita income ^{b)}	2,838	408	0.14	4.813	1.915

Notes: a) expressed in thousands

b) expressed in thousands of yen.

Table 2. Distribution of victims

Percentile	
10	1
20	5
30	12.7
40	26.6
50	67
60	139
70	266
80	594
90	1645

Table 3 Determinants of the number of victims (Zero inflated negative-binominal model)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1Year	3Years	5 Years	1 Year	3 Years	5 Years	1 Year	3 Years	5 Years	1 Year	3 Years	5 Years
<i>NDIS</i>	0.41** (3.90)	0.42** (3.85)	0.42** (3.88)	0.41** (3.89)	0.42** (3.86)	0.42** (3.88)	0.41** (3.86)	0.42** (3.83)	0.42** (3.89)	0.41** (3.87)	0.42** (3.84)	0.42** (3.88)
<i>AVNDIS</i>	-0.05* (-1.95)	-0.06* (-1.96)	-0.02 (-1.02)									
<i>PBATH</i>	-0.004 (-0.02)	0.06 (0.23)	0.02 (0.07)	0.09 (0.33)	0.11 (0.40)	0.02 (0.08)	0.06 (0.24)	0.08 (0.30)	0.001 (0.001)	0.04 (0.17)	0.08 (0.31)	0.01 (0.06)
<i>PBATH*</i>				-0.06** (-7.49)	-0.04* (-1.96)	-0.01 (-0.64)						
<i>AVNDIS</i>												
<i>CENTE</i>	-0.36** (-2.60)	-0.38** (-2.72)	-0.31* (-2.17)	-0.34** (-2.54)	-0.37** (-2.70)	-0.33* (-2.23)	-0.26* (-1.74)	-0.29* (-2.14)	-0.33* (-2.11)	-0.35** (-2.60)	-0.38** (-2.76)	-0.31* (-2.13)
<i>CENTE*</i>							-0.05** (-2.95)	-0.07** (-2.58)	-0.003 (-0.37)			
<i>AVNDIS</i>												
<i>FFIGHT</i>	-0.12 (-0.47)	-0.10 (-0.37)	-0.12 (-0.45)	-0.13 (-0.49)	-0.11 (-0.41)	-0.13 (-0.48)	-0.16 (-0.59)	-0.12 (-0.44)	-0.13 (-0.50)	-0.06 (-0.26)	-0.06 (-0.22)	-0.10 (-0.39)
<i>FFIGHT*</i>										-0.08** (-8.81)	-0.05* (-2.24)	-0.02 (-0.99)
<i>AVNDIS</i>												
<i>POLIC</i>	0.24 (1.02)	0.25 (1.06)	0.25 (1.07)	0.24 (1.05)	0.25 (1.05)	0.25 (1.09)	0.27 (1.16)	0.25 (1.08)	0.26 (1.10)	0.26 (1.11)	0.25 (1.07)	0.25 (1.08)
<i>IMIG</i>	0.84* (2.15)	0.93* (2.31)	0.85* (2.15)	0.87* (2.21)	0.90* (2.25)	0.83* (2.09)	0.84* (2.13)	0.89* (2.25)	0.81* (2.04)	0.87* (2.21)	0.92* (2.28)	0.84* (2.12)
<i>POP</i>	4.47** (4.46)	4.50** (4.54)	4.44** (4.46)	4.49** (4.54)	4.43** (4.49)	4.42** (4.44)	4.58** (4.62)	4.48** (4.55)	4.41** (4.43)	4.50** (4.54)	4.44** (4.50)	4.42** (4.43)
<i>PORAT</i>	0.31 (1.41)	0.29 (1.29)	0.32 (1.40)	0.32 (1.43)	0.30 (1.30)	0.32 (1.49)	0.32 (1.44)	0.28 (1.25)	0.33 (1.45)	0.29 (1.31)	0.28 (1.23)	0.32 (1.40)
<i>OLDRAT</i>	1.60* (1.67)	1.69* (1.76)	1.64* (1.70)	1.62* (1.70)	1.72* (1.79)	1.66* (1.73)	1.59* (1.66)	1.70* (1.77)	1.67* (1.73)	1.59* (1.67)	1.72* (1.79)	1.64* (1.70)
<i>INCOM</i>	-3.89** (-2.92)	-4.21** (-3.21)	-4.15** (-3.14)	-3.98** (-3.05)	-4.30** (-3.24)	-4.16** (-3.13)	-4.09** (-3.11)	-4.33** (-3.29)	-4.14** (-3.11)	-4.08** (-3.12)	-4.37** (-3.28)	-4.18** (-3.16)
<i>Year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Logit Model												
<i>NDIS</i>	4.58* (2.21)	4.59* (2.28)	4.56* (2.22)	4.51* (2.20)	4.56* (2.25)	4.58* (2.22)	4.49* (2.15)	4.49* (2.24)	4.60* (2.22)	4.51* (2.21)	4.58* (2.27)	4.56* (2.21)
<i>NDIS*</i>	-0.22 (-0.83)	-0.22 (-0.87)	-0.21 (-0.83)	-0.21 (-0.81)	-0.22 (-0.85)	-0.22 (-0.83)	-0.20 (-0.76)	-0.21 (-0.83)	-0.22 (-0.84)	-0.21 (-0.82)	-0.22 (-0.87)	-0.21 (-0.83)
<i>Ln(INCOM)</i>												
<i>NDIS*</i>	-0.21** (-2.77)	-0.21** (-2.90)	-0.21** (-2.88)	-0.21** (-2.91)	-0.21** (-2.90)	-0.21** (-2.87)	-0.21** (-2.91)	-0.21** (-2.91)	-0.21** (-2.86)	-0.21** (-2.79)	-0.21** (-2.90)	-0.21** (-2.87)
<i>Ln(POP)</i>												
α	2.57**	2.57**	2.57**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**

	(45.8)	(45.8)	(45.8)	(45.9)	(45.9)	(45.9)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)
Samples	658	658	658	658	658	658	658	658	658	658	658	658
Non-zero samples	604	604	604	604	604	604	604	604	604	604	604	604

Notes: Each column of this table reports a separate estimate of a zero inflated negative binominal model. As discussed in the text, this model has two equations. The lower panel of the table reports the logit model estimates of the probability that nobody becomes a victim of a natural disaster. The upper panel reports the results from the negative binominal regression where numbers are elastic and are evaluated at the sample mean values of the dependent and each independent variable, and values in parentheses are z-statistics calculated by the delta method using robust standard errors. * and ** denote significance at the 5% and 1% levels, respectively. In each estimate, constants, year dummies, rates of primary industry populations, number of households, and hours of sunlight are included but not reported to save space

Table 4. Determinants of the number of victims (Zero inflated negative-binominal model) Number of victims<100

	(1) 1Year	(2) 3Years	(3) 5 Years	(4) 1 Year	(5) 3 Years	(6) 5 Years	(7) 1 Year	(8) 3 Years	(9) 5 Years	(10) 1 Year	(11) 3 Years	(12) 5 Years
<i>NDIS</i>	0.18 (1.10)	0.19 (1.24)	0.19 (1.21)	0.18 (1.13)	0.19 (1.20)	0.18 (1.19)	0.18 (1.09)	0.18 (1.17)	0.18 (1.18)	0.18 (1.08)	0.19 (1.17)	0.19 (1.21)
<i>AVNDIS</i>	-0.03** (-3.66)	-0.07* (-1.81)	-0.01 (-0.66)									
<i>PBATH</i>	0.05 (0.23)	0.06 (0.25)	0.02 (0.08)	0.09 (0.37)	0.13 (0.53)	0.02 (0.12)	0.08 (0.33)	0.10 (0.39)	0.02 (0.01)	0.07 (0.32)	0.08 (0.35)	0.02 (0.08)
<i>PBATH*</i> <i>AVNDIS</i>				-0.02** (-4.31)	-0.04* (-1.99)	-0.004 (-0.29)						
<i>CENTE</i>	-0.20* (-1.79)	-0.19* (-1.73)	-0.17 (-1.42)	-0.19* (-1.76)	-0.17 (-1.57)	-0.18 (-1.48)	-0.15 (-1.34)	-0.12 (-0.92)	-0.18 (-1.47)	-0.20* (-1.85)	-0.19* (-1.72)	-0.16 (-1.36)
<i>CENTE*</i> <i>AVNDIS</i>							-0.02* (-1.87)	-0.03 (-0.91)	-0.001 (-0.21)			
<i>FFIGHT</i>	-0.22 (-1.17)	-0.21 (-1.14)	-0.22 (-1.16)	-0.22 (-1.19)	-0.23 (-1.22)	-0.22 (-1.17)	-0.22 (-1.15)	-0.22 (-1.18)	-0.22 (-1.17)	-0.19 (-1.00)	-0.15 (-0.80)	-0.21 (-1.09)
<i>FFIGHT*</i> <i>AVNDIS</i>										-0.03** (-5.87)	-0.06** (-2.83)	-0.01 (-0.86)
<i>POLIC</i>	-0.17 (-1.36)	-0.16 (-1.28)	-0.17 (-1.32)	-0.17 (1.39)	-0.17 (-1.36)	-0.17 (-1.33)	-0.16 (-1.32)	-0.16 (-1.28)	-0.17 (1.33)	-0.17 (-1.39)	-0.16 (-1.28)	-0.17 (-1.32)
<i>IMIG</i>	0.05 (0.18)	0.04 (0.15)	-0.02 (-0.08)	0.04 (0.15)	0.03 (0.13)	-0.01 (-0.06)	0.03 (0.12)	0.01 (0.06)	-0.01 (-0.06)	0.07 (0.25)	0.07 (0.23)	-0.02 (-0.08)
<i>POP</i>	1.43* (2.23)	1.59** (2.43)	1.31* (2.07)	1.36* (2.13)	1.48* (2.31)	1.29* (2.03)	1.40* (2.22)	1.48* (2.25)	1.28* (2.01)	1.38* (2.19)	1.58** (2.47)	1.30* (2.06)
<i>PORAT</i>	0.14 (1.05)	0.14 (1.05)	0.14 (1.01)	0.13 (0.97)	0.14 (1.01)	0.13 (0.99)	0.13 (0.98)	0.14 (1.01)	0.13 (0.98)	0.12 (0.92)	0.13 (0.94)	0.14 (1.00)
<i>OLDRAT</i>	-1.00 (-1.41)	-1.05 (-1.47)	-1.12 (-1.52)	-1.01 (-1.41)	-1.05 (-1.46)	-1.09 (-1.48)	-1.07 (-1.50)	-1.12 (-1.53)	-1.08 (-1.48)	-1.01 (-1.43)	-1.06 (-1.49)	-1.14 (-1.55)
<i>INCOM</i>	0.77 (0.69)	0.86 (0.77)	0.80 (0.71)	0.68 (0.62)	0.76 (0.69)	0.75 (0.67)	0.73 (0.66)	0.79 (0.71)	0.74 (0.67)	0.68 (0.61)	0.78 (0.70)	0.80 (0.71)
<i>Year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Logit Model												
<i>NDIS</i>	2.86* (1.83)	2.95* (1.86)	2.87* (1.87)	2.85* (1.84)	2.85* (1.85)	2.86* (1.82)	2.79* (1.83)	2.81* (1.83)	2.86* (1.82)	2.85* (1.84)	2.90* (2.27)	2.58* (1.81)
<i>NDIS*</i> <i>Ln(INCOM)</i>	-0.45 (-0.17)	-0.05 (-0.19)	-0.04 (-0.15)	-0.04 (-0.16)	-0.04 (-0.16)	-0.04 (-0.15)	-0.03 (-0.13)	-0.03 (-0.13)	-0.04 (-0.15)	-0.04 (-0.18)	-0.04 (-0.18)	-0.04 (-0.15)
<i>NDIS*</i> <i>Ln(POP)</i>	-0.18** (-2.44)	-0.19** (-2.41)	-0.19*** (-2.42)	-0.18** (-2.46)	-0.19** (-2.44)	-0.19** (-2.43)	-0.18** (-2.45)	-0.19** (-2.42)	-0.19** (-2.43)	-0.18** (-2.46)	-0.18** (-2.43)	-0.19** (-2.42)
α	2.57**	2.57**	2.57**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**

	(45.8)	(45.8)	(45.8)	(45.9)	(45.9)	(45.9)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)
Samples	355	355	355	355	355	355	355	355	355	355	355	355
Non-zero samples	301	301	301	301	301	301	301	301	301	301	301	301

Notes: Each column of this table reports a separate estimate of a zero inflated negative binominal model. As discussed in the text, this model has two equations. The lower panel of the table reports the logit model estimates of the probability that nobody becomes a victim of a natural disaster. The upper panel reports the results from the negative binominal regression where numbers are elastic and are evaluated at the sample mean values of the dependent and each independent variable, and values in parentheses are z-statistics calculated by the delta method using robust standard errors. * and ** denote significance at the 5% and 1% levels, respectively. In each estimate, constants, year dummies, rates of primary industry' populations, number of households, and hours of sunlight are included but not reported to save space